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AUTHOR Harnisch, Delwyn L.
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ABSTRACT

A structural model suggesting complex causal interrelationships among eight variables which contribute to variance in student learning is described. The variables include mother's and father's educational level; Relaxed Test Comfort Score; Specific Math Comfort Score: Attitudinal Continuing Motivation Score; Behavioral Continuing Motivation Score; Criterion Scaling of Success Attribution on Test Score; and Total Math Score. The data set used to investigate the fit of the model consists of the test results of 2,109 eleventh grade students who took the 1978 Illinois Inventory of Educational Progress, a statewide assessment program. The method of covariance structure analysis was applied to reveal the causal relation among factors including student background motivation and learning outcomes. The model indicates that student motivation and student learning outcomes are most directly affected by student background. Further observations show an indirect influence on student learning outcomes as mediated by the student motivation factor. (Author/AL)

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Delwyn L. Harnisch

University of Illinois at Urbana-Champaign

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Paper presented as part of a symposium entitled, "Eliminating Motivational Test Bias in Educational Testing," American Educational Research Association, Los Angeles, April 1981. Chair: Martin L. Maehr; Organizer: Kennedy T. Hill; Presenters: James Plass, Allan Wigfield, Shelley Hymel, Andrew Hartman, Delwyn L. Harnisch.

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A Test of a Structural Model of Student Background and Motivation Variables Influencing Student Test Performance

Delwyn L. Harnisch

Many variables impinging on students and their background affect their learning outcome. These variables include parents, peers, teachers, schools, and student motivation. Typically, only a small subset of the potential influence is investigated in a single study. The monumental Equality of Educational Opportunity (EEO) study (Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld, & York, 1966; Mayeske, Wisler, Beaton, Weinfeld, Cohen, Okada, Proshek, & Tabler, 1972), stands out as one of the more comprehensive efforts of collecting information on the various factors affecting student learning. This report found locus of control to be the best predictor of achievement among a great number of student, social, teacher, and school factors. This finding from the Coleman study reminded educators and researchers of the critical importance of motivation and related concepts of self.

Previous research reviews similarly concluded that motivation is a critical variable in understanding student learning (Crandall, 1963; Weiner, 1976; Bar-Tal, 1978; Uguroglu & Walberg, 1979; Hill, 1980; Walberg & Uguroglu, 1980). The purpose of this paper is to present recent methodological advances which integrate concerns of measurement, statistics and motivation theory into one conceptual, analytic framework. More specifically, this paper applies the method of covariance structure analysis (for a review, see Bentler, 1980) to a statewide data set in order to evaluate the causal relation between student characteristics, motivation, and achievement. According to Centra and Potter (1980), structural analysis techniques are the most powerful tools available to the educational researcher.

The Model

In this paper I present a structural model depicting the relationships among eight variables which contribute to variance in student learning. Two variables, mother's and father's educational level (ME and FE), represent the student background factor while five variables, Relaxed Test Comfort Score (RTC), Specific Math Comfort Score (SPM), Attitudinal Continuing Motivation Score (ACM), Behavioral Continuing Motivation Score (BCM), and Criterion Scaling of Success Attribution on Test Score (CSS), represent the student motivation factor and the one variable, Total Math Score (TMS), represents the student learning outcome factor.

A structural model describes potential causal relationships between underlying factors. In Figure 1, the respective variables are shown corresponding to a factor while the expected causal relationships are indicated by straight-line arrows.

The structural model indicates that student motivation and student learning outcomes are most directly affected by student background. Student background also has an indirect influence on student learning outcomes as mediated by the student motivation factor.

The Sample

The data set used to investigate the fit of the structural model was the test results from the 1978 Illinois statewide assessment program. This annual statewide survey, known as the Illinois Inventory of Educational Progress (IIEP), provides data for some 6,300 students from a random sample of approximately 110 schools at each of the fourth-, eighth-, and eleventh-grade levels. At each of the attendance centers, between 18 and 22 students are randomly selected for the grade level being tested at the

school. This gives an approximate statewide sample of 2,100 students per grade level (4, 8, and 11). The total IIEP state survey sampling, then, involves some 6,300 students spread evenly across the elementary (4th), junior high (8th), and high school (11th) grades being tested.

The data set includes item response data for tests of reading and mathematics. Also included are questionnaire responses which provide data on student background, self-report of test anxiety, their attributions for success and failure on tests, and other specific and general motivation variables. The results presented below are based on intercorrelations of eight variables for 2,109 students at the eleventh grade.

The Variables

The student background factor consists of two variables of parents' education level which allowed for responses to vary from "did not complete the eighth grade" to "has a masters or doctoral degree." The single student learning outcome factor was represented by one variable which was the total number of math items correct out of a possible 49 items.

The student motivation factor includes five variables. Three of the five variables were asked prior to the taking of the math test while two variables were asked following the math test. The three variables asked prior to taking the test were the Relaxed Test Comfort Score, Success Attribution on Tests, and Specific Math Comfort Score. Seven items formed the Relaxed Test Comfort Score (see Appendix A for a listing of the seven items) with the estimate of reliability (Cronbach's alpha) for the Relaxed Test Comfort scale being .71 with our data. The success attribution variable had four response categories to the question of "When you do well on a test in school is it because (1) you are smart, (2) you studied very hard, (3) you were lucky, or (4) the test was easy?" Since this is a nominal

variable, its present characteristics do not allow for meaningful correlations to be found with other interval scale variables. To alleviate this problem, a criterion scaling approach (Beaton, 1969) was taken for the responses to this question. The criterion used was the total math score such that students attributing their success on tests to the response "you are smart" were given the mean total math score for students selecting this respective response. Similarly, students selecting other response alternatives to this question were given the respective mean total math score. The Specific Math Comfort Score variable was composed of two items whose responses were added to form the respective score. The two items represented in this score are, "When the teacher is teaching you about math, do you feel that you understand him/her better than other children in the class?" and "When you are out of school and you are thinking about your math lessons for the next day, do you feel sure that you will get the answers right when the teacher calls on you?"

The first of two variables asked after taking the math test followed immediately after the test administrators announced that students had completed the mathematics section of the test. Three minutes of silence were given between the mathematics and reading test sections for students to simply remain quiet or do additional math exercises provided. The Behavioral Continuing Motivation Score indicates the additional number of mathematic items attempted during the silence period break between tests.

The last variable of the student motivation factor, Attitudinal Continuing Motivation Score, was asked of students at the close of the total testing period. This variable represents their responses to the question of "If you would like to do more mathematics exercises, about

how many would you like to do? (1) none, (2) 1-10, (3) 11-20, (4) 21-30, (5) 31-40, (6) 41-50, and (7) 51 or more."

Description of Model

The model being tested in this study is based on the intercorrelation matrix of the eight variables given in Table 1 for the 2,109 11th-grade students. The model investigated in this study is summarized in Figure 1. The boxes in the figure represent the measurements while the circles represent the hypothetical constructs underlying the measurements. The straight-line arrows from the constructs (circles) to their respective measurements (boxes) indicate that the constructs cause the performance on the measures and are analagous to factor loadings from a factor analysis. Unidentified sources of variation in the model, including random error, are represented in the figure by lower case e for the variables measuring the endogenous constructs and by δ for the two variables identified with the single exogenous construct.

The straight-line arrows between constructs represent hypothesized causal relationships. Thus, for each construct an equation can be written. The equation expresses that construct in terms of other variables in the model plus a disturbance term. The disturbance term, ϕ_1, ψ_1, and ψ_2, represents random error and systematic variation not represented in the model. The strength of causal paths, γ_1, γ_2, and β_1 are measured by standardized regression coefficients. Finally, a correlation matrix is given which indicates the relationship among the constructs being tested in the model.

The chi-square test determines whether the observed data fit the proposed, theoretical model. A non-significant chi-square value suggests a reasonable fit between the model and the data while a significant chi-square

value suggests that the data are inconsistent with the model. In addition to the chi-square test, the observed variance matrix was compared to the estimated variance-covariance matrix. This difference between the observed and estimated is called the residual matrix. Small entries in the residual matrix would imply a good fit between the model and the data. In keeping with good practice, evaluation of the residual matrix was conducted since the chi-square test may be significant due to the great power given by the large sample size but the fit may be quite good as judged by small residuals. It can be said that in general, statistical significance alone does not imply substantive significance. The residual matrix provides some assistance in judging whether a statistically significant lack of fit is also substantially significant. Summarization of the residual matrix was performed by computing the square root of the mean squared residuals.

To evaluate the nearness of fit of the proposed model to the data, a test of the proposed model with a null model of complete independence was conducted using the incremental fit indices discussed in detail by Bentler and Bonett (1980). This evaluation approach of the proposed model aids the researcher in making conclusions about the model despite the possible rejection of the hypothesis given the chi-square test. In addition, other models of interest can be compared with the null model of complete independence and with each other to evaluate the possible gain in one model over another.

Recent advances in the analysis of covariance, make it possible to test hypotheses about structure simultaneously in one statistical model (Linn & Werts, 1979; Bentler, 1980; Shavelson & Stuart, 1980). The advantages of this approach over factor analyses and regression analyses are that: (1) statistical tests of the structure of the motivation

measures can be conducted, and (2) each statistical test can be made while controlling for variation in other parts of the model. To compare the structural model with the data, LISREL IV (Jöreskog & Sörbom, 1978), a statistical program was used to test the model in Figure 1.

Results and Discussion

An analysis of the fit of the model in Figure 1 to the data on student background, student motivation, and student learning outcome resulted in a significant chi-square value ($\chi^2 = 159.10$, df = 18, $p < .001$). The significant chi-square value suggests a nonreasonable fit between the model and the data. In addition to the chi-square test, comparisons were made between the observed correlation matrix and the estimated correlation matrix. This difference between the observed and the estimated is called the residual matrix with its values given in Table 2. The range of residuals is from -.100 to .078. The residual matrix is summarized by computing the square root of the mean squared residuals. The result of this summary statistic is a value of .012 which indicates that the range of discrepancies between the model and the data are not quite as large as one might be led to believe they would be based solely on the chi-square test.

A comparison of the proposed model in Figure 1 with a null model of complete independence was made using the incremental fit indices described by Bentler and Bonett (1980). The results of computing these statistics are shown in Table 3. The two statistics used in the evaluation of the model are a non-normed fit index, $\hat{\rho}_{oi}$, and a normed fit index, $\hat{\Delta}_{oi}$. The procedures used in computing these statistics from your model χ^2 test values are also shown in Table 3. The range of $\hat{\Delta}_{oi}$ is from 0 to 1, i.e., $0 \leq \hat{\Delta}_{oi} \leq 1$, so .921 on the normed fit statistic indicates there is not

much room for improvement of fit (1 - .921 = .079) and that we are doing quite well with our model of interest despite the rejection of it based on the χ^2 test. If there is specification error in the model tested, it is small. That is, the .921 value indicates the extent of the covariance among observed variables which has been accounted for by the model of interest.

The correlation among the constructs given in Table 4 reveals a correlation of .58 between student motivation and student learning outcome. This relationship indicates that multiple measures of motivation do improve predictions of achievement. I would add that more valid measures of motivation rather than more internally consistent of homogeneous single measures would even aid in the prediction of student learning outcome.

The weight beside the arrows for the constructs in Figure 2 summarize the result of the analysis of student background, student motivation and student learning outcomes. The direct effect, .279, of student background on student learning and the indirect effect, .257, are of similar magnitude. Student motivation correlates at a value of .506 with student learning outcomes when controlling for the background of a student indicating its significant contribution over and above ones understanding of achievement with student background.

The measurement model for motivation reveals weights ranging from .24 to .59 on the construct. Highest loadings on the motivation construct were found on the success attribution variables (.59) and the Relaxed Test Comfort Score (.48). The lowest loading on the motivation construct was found with the Behavior Continuing Motivation Score (.24).

Summary

The results of this study indicate the importance of the student motivation factor in understanding student learning outcomes. Student background factor contributes nearly an equal amount to both the student learning outcome factor and the student motivation of factor. Controlling for the student background factor, it was found that the student motivation factor accounted for an additional 26% of the student learning outcome variance.

The structural model presented in this paper can be very useful in further research on understanding the contribution of student background and student motivation on student learning outcomes. The proposed model described predicted causal relations among eight variables where the predictions are based on previous research. The structural analysis was used to test how well the data fit the proposed model. Structural analysis techniques, which integrate concerns of measurement, statistics, and motivation theory into one conceptual, analytic framework, were applied to a data set of 2,109 11th-grade students revealing the interrelationship among factors including student background, motivation, and learning outcomes.

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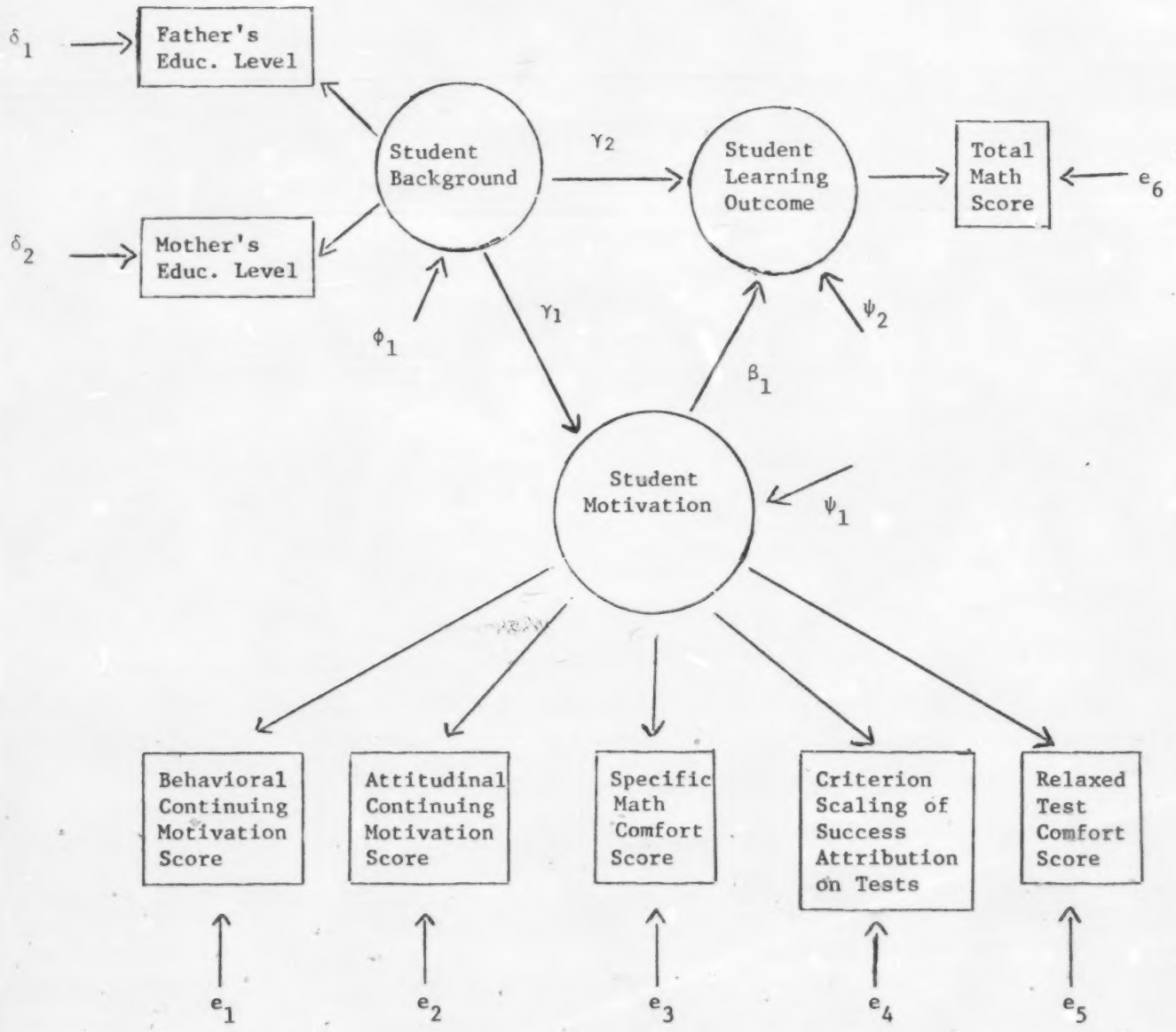

Figure 1. Structural Model of Student Background, Motivation and Achievement

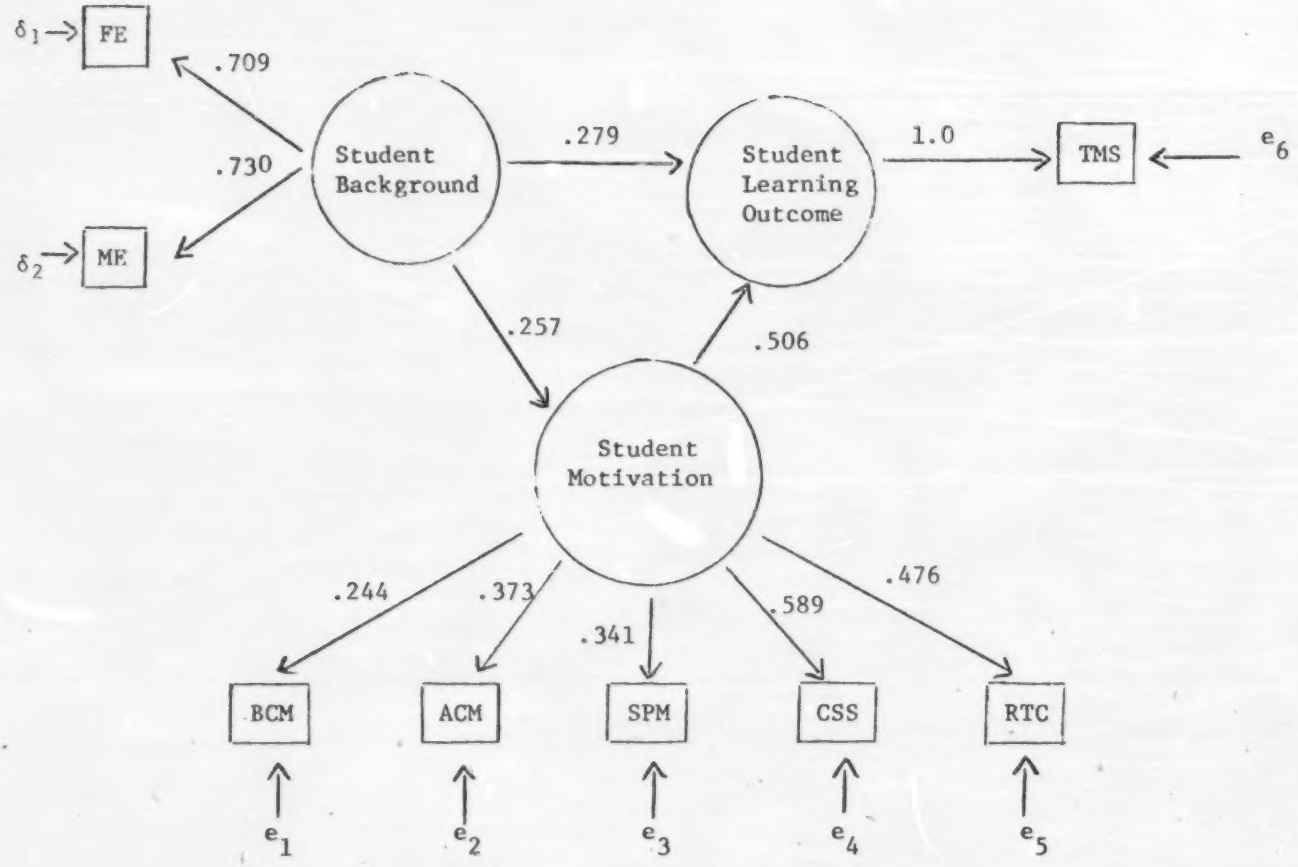

Figure 2. Estimates of Path Coefficients for Structural Model of Student Background, Motivation and Achievement

Where FE = Father's Educational Level
ME = Mother's Educational Level
TMS = Total Math Score
BCM = Behavioral Continuing Motivation Score
ACM = Attitudinal Continuing Motivation Score
SPM = Specific Math Comfort Score
CSS = Criterion Scaling of Success Attribution on Tests
RTC = Relaxed Test Comfort Score

Table 1

Correlation Matrix of Student Background, Motivation and Achievement Variables (N = 2109)

	1	2	3	4	5	6	7	8
1. Father's Education Level (FE)	1.00							
2. Mother's Education Level (ME)	.52	1.00						
3. Attitudinal Continuing Motivation Score (ACM)	.06	.04	1.00					
4. Behavioral Continuing Motivation Score (BCM)	.04	.02	.16	1.00				
5. Specific Math Comfort Score (SPM)	.03	.05	.17	.12	1.00			
6. Criterion Scaling Success Attribution on Tests (CSS)	.15	.14	.12	.13	.20	1.00		
7. Relaxed Test Comfort Score (RTC)	.06	.08	.18	.08	.24	.30	1.00	
8. Total Math Score (TMS)	.29	.30	.28	.13	.11	.38	.23	1.00

Table 2

Residual Matrix of Student Background, Motivation and Achievement Variables

	1	2	3	4	5	6	7	8
1. Father's Education Level (FE)	.000							
2. Mother's Education Level (ME)	.000	.000						
3. Attitudinal Continuing Motivation Score (ACM)	-.030	-.008	.000					
4. Behavioral Continuing Motivation Score (BCM)	-.026	-.004	.069	.000				
5. Specific Math Comfort Score (SPM)	-.014	-.032	.043	.037	.000			
6. Criterion Scaling Success Attribution on Tests (CSS)	.029	.043	-.100	-.014	-.001	.000		
7. Relaxed Test Comfort Score (RTC)	-.010	-.027	.002	-.036	.078	.019	.000	
8. Total Math Score (TMS)	.000	.000	.064	-.011	-.087	.040	-.045	.000

Table 3

Evaluation of Model in Figure 1

Model Test*			Model Comparison				
Model	χ^2	df	Comparison	χ^2	df	$\hat{\rho}_{oi}$	$\hat{\Delta}_{oi}$
M_o	2003.04	28	$M_o - M_i$	1843.93	10	.889	.921
M_i	159.10	18					

*$p < .001$ for both chi-square statistics

where $$\hat{\rho}_{oi} = \frac{\frac{\chi^2_o}{df_o} - \frac{\chi^2_i}{df_i}}{\frac{\chi^2_o}{df_o} - 1}$$, non-normed fit index

$$\hat{\Delta}_{oi} = \frac{\chi^2_o - \chi^2_i}{\chi^2_o}$$, normed fit index

M_o = Null model of modified independence

M_i = Model of interest as shown in Figure 1

$M_o - M_i$ = Increment in fit of M_i over null model

Table 4

Correlation Matrix Among Constructs

	1	2	3
1. Student Background	1.00		
2. Student Motivation	.26	1.00	
3. Student Learning Outcome	.41	.58	1.00

Appendix A

7-Item Relaxed Form of TASC

NAME _____ DATE _____

Directions: Circle the letter which best describes your response for the following:

1. When the teacher says that she is going to give the class a test, do you feel relaxed and comfortable?

   a. Yes
   b. No

2. Do you feel relaxed before you take a test?

   a. Yes
   b. No

3. Do you feel relaxed while you are taking a test?

   a. Yes
   b. No

4. Do you feel relaxed when the teacher says that she is going to ask you questions to find out how much you know?

   a. Yes
   b. No

5. When the teacher says that she is going to give the class a test, do you usually feel that you will do good work?

   a. Yes
   b. No

6. While you are taking a test, do you usually think you are doing good work?

   a. Yes
   b. No

7. Do you like tests in school?

   a. Yes
   b. No